# Complex Mortgages\*

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#### Abstract

We investigate the characteristics and the default behavior of households who take out complex mortgages. Unlike traditional fixed-rate or adjustable rate mortgages, complex mortgages are not fully amortizing and enable households to postpone loan repayment. We find that complex mortgages are used by sophisticated households with high income levels and prime credit scores, in contrast to the low income population targeted by subprime mortgages. Complex mortgage borrowers have significantly higher delinquency rates than traditional mortgage borrowers even after controlling for leverage, payment resets, and other household and loan characteristics, suggesting a role for adverse selection of borrowers into complex mortgage contracts. The difference in the delinquency rates between complex and traditional borrowers increases with measures of financial sophistication (like income or credit scores) or strategic default (like the LTV ratio). These results suggest that complex borrowers are more strategic in their default decisions than traditional borrowers.

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## 1 Introduction

Over the last decade, the residential mortgage market has experienced a significant increase in product complexity, followed by a rapid reversion back to simpler products. The newly popular set of products featured zero or negative amortization, short interest rate reset periods, and low introductory teaser interest rates. We term these "complex mortgages" (CM). Figure 1 shows the proportion of fixed rate (FRM), adjustable rate (ARM), and complex mortgage products originated between 1995 and 2009, as reported by LPS Applied Analytics (our primary data source described in detail below). The share of complex mortgages in the U.S. remained below 2% until the second half of 2003 before jumping to about 30% of mortgage originations just two years later.

While some have conjectured the link between complex mortgages and the recent crisis, there has been relatively little academic work on the innovations in mortgage contract design. Instead, researchers have focused on securitization and the expansion of credit to subprime borrowers (Mian and Sufi (2009), Keys, Mukherjee, Seru, and Vig (2010), and Jiang, Nelson, and Vytlacil (2010b)). We fill this gap by studying the characteristics of individual households that obtain complex mortgages and their subsequent default behavior.

Complex mortgages are sometimes portrayed by the media as predatory products that were pushed by financial institutions to take advantage of naive households who did not fully understand the contract terms.<sup>1</sup> We show that this characterization is far from accurate. Rather, our results suggest that complex loans attracted relatively financially sophisticated households with high credit scores and favorable income characteristics. Moreover, these households are stretching their borrowing capacity, as indicated by their higher value-to-income (VTI) ratios. They also exhibit stronger tendency to exercise the default option, leading to delinquency rates well beyond those for traditional mortgage borrowers with similar characteristics like

<sup>&</sup>lt;sup>1</sup>See, for example, the New York Times article, *How Countrywide Covered the Cracks*, by Gretchen Morgenson, October 16, 2010, at http://www.nytimes.com/2010/10/17/business/17trial.html.

income, FICO, and leverage ratios. The apparent dissonance between the popular perception and observed outcomes allows us to shed some light on the following questions: Did the wide introduction of complex mortgages represent an information-distorting lending process that resulted in deadweight losses? Or was it a market innovation with a bad ex post realization brought on by the financial crisis?

Our primary data source is the LPS Analytics data. The database, described in detail in Section 2, contains loan level information for a large sample of mortgages in the United States. Of particular relevance for our analysis is the ability to identify precise contract terms at the time of loan origination and realized payment behavior over the lifetime of the loan.

We first investigate the characteristics of households that take out complex mortgages. The defining feature of complex mortgages is the deferral of principal repayment. Complex mortgages are characterized by low initial payments during the first few years of the contract and a significant increase in payments after mortgage resets, which typically occur after three to five years. A priori, complex mortgage products might be appealing to both sophisticated and unsophisticated households.

On the one hand, the low initial payments might obfuscate the long-term borrowing costs for households (Gabaix and Laibson (2006), Carlin (2009), Carlin and Manso (2010), and Stango and Zinman (2011)). Lenders might have an incentive to introduce complex products to shroud the total costs of borrowing via intricate reset schedules, prepayment penalties, and short-lived teaser interest rates. They might be particularly eager to offer these products if they are confident in their ability to securitize them. In this case, we should observe that complex mortgages are taken out primarily by unsophisticated households that do not understand the specific features of their contracts.

On the other hand, complex mortgages might be a hallmark of sophisticated borrowers.

The low initial payments of complex mortgages can relax household liquidity and borrowing constraints and enable households to take larger exposures in housing assets. These products

can be optimal borrowing instruments if households expect their income levels or housing prices to increase over time (Cocco (2010)), Gerardi, Rosen, and Willen (2010), and Piskorski and Tchistyi (2010)). Postponing the amortization of a mortgage might also have tax benefits for high-income households due to the deductibility of mortgage interest from taxable income (Amromin, Huang, and Sialm (2007)). Moreover, complex mortgages might be preferred by households that are less averse to defaulting in case of unfavorable income and house price shocks. These households might be more risk seeking in general or be less influenced by ethical norms to pay back their debt (Guiso, Sapienza, and Zingales (2009)). By minimizing the initial mortgage payments and keeping a high mortgage balance, these households maximize the value of the default option. The incentive to exercise this option should be stronger for non-recourse mortgages, where lenders do not have access to the non-collateralized household assets in case of delinquency.

Using the LPS Analytics data, we find that such mortgages are used by sophisticated households with high income levels and prime credit scores. Therefore, this group of borrowers is distinct from the subprime borrowers that have received much attention in recent studies. We also find that geographic areas with higher past house price appreciation, with higher population growth, and with a higher proportion of young households have a greater proportion of complex mortgages, suggesting that the expectation of continued house price appreciation and income growth is a likely driving force behind the popularity of CM contracts. Complex loans are also more prevalent in non-recourse states, where non-collateralized assets of the households are protected. These results indicate that complex loans are originated to financially sophisticated households that are less likely to be fooled by predatory lending practices.

We next study the default behavior of CM borrowers. We posit that complex mortgages might have different delinquency rates because of differences in their contractual design or because of inherent differences in default propensities of households that self select into such contracts. The contractual design of complex mortgages can change the delinquency rate for two reasons. First, CM payments can change significantly over time, as low initial payments on back-loaded contracts rise after amortization resets. Thus, defaults on complex mortgages might initially be lower than defaults on fully-amortizing contracts, but increase following resets. Households who are already stretching to meet the initial payments might have difficulty meeting the additional monthly payments, especially if they experience unfavorable income or expenditure shocks. This type of default is termed a "cash flow default." Second, the lack of amortization inevitably leads to higher loan-to-value ratios for any given path of house prices. Rational households might optimally choose to default on their mortgages when the current value of the house is lower than the remaining loan balance even if they have sufficient income to cover the payments. This type of default is termed a "strategic default." Therefore, the back loaded feature of complex mortgages can affect both cash flow and strategic defaults. Finally, complex mortgages might also attract a different borrower clientele, as described above. This clientele, characterized by greater sophistication and willingness to exercise their default option, might generate higher delinquency rates, holding loan and borrower characteristics fixed.

We find that complex mortgages indeed have significantly higher unconditional delinquency rates than both FRM and ARM contracts after the first 18 months since mortgage origination. Households that self select into complex mortgages appear to be different from other households. Even after controlling for leverage, payment resets, and other household and loan characteristics, we find significantly higher default rates among CM borrowers. The difference in the delinquency rates between complex and traditional borrowers increases both with measures of financial sophistication (like income or credit scores) and measures of strategic default (like the LTV ratio). Moreover, complex borrowers exhibit a smaller increase in the probability of declaring bankruptcy after defaulting on their mortgages than traditional borrowers. To the extent that declaring personal bankruptcy is an indication of financial constraints, com-

plex mortgage borrowers who become delinquent on their mortgages tend to be less distressed than other types of borrowers. In summary, these findings suggest that complex borrowers tend to be more strategic in their default decisions than other types of mortgage borrowers.

Overall, our findings suggest that complex mortgages are a significant driving force behind the mounting defaults during the recent crisis. The role of mortgage security design is distinct from the well-documented impact of subprime mortgages and securitization, since complex mortgages are taken out mainly by prime households and since the probability of securitization is lower for complex mortgage contracts than for fully-amortizing contracts.<sup>2</sup>

A few recent papers have investigated the role of non-traditional mortgage contracts in the recent crisis. Piskorski and Tchistyi (2010) study optimal mortgage design in an environment with risky privately observable income and costly foreclosure and show that the features of the optimal mortgage contract are consistent with an option adjustable rate mortgage contract. Corbae and Quintin (2010) present a model where heterogeneous households select from a set of mortgage contracts and have a choice of defaulting on their payments. Using their model, they find that the presence of subprime mortgages with low down payments substantially amplifies foreclosure rates in the presence of a large exogenous shock to house prices. In a contemporaneous paper, Barlevy and Fisher (2010) describe a rational expectations model in which both speculators and their lenders use interest-only mortgages when there is a bubble in house prices. They provide evidence that interest only mortgages were used extensively in cities where inelastic housing supply enables pronounced boom-bust cycles. Our paper studies empirically the characteristics and the default experiences of borrowers of complex loans.

<sup>&</sup>lt;sup>2</sup>In addition to papers cited earlier, the literature on securitization and the expansion of credit to subprime borrowers includes Adelino, Gerardi, and Willen (2009), Bond, Musto, and Yilmaz (2009), Deng and Quigley (2009), Keys, Mukherjee, Seru, and Vig (2009), Loutskina and Strahan (2009), Mayer, Pence, and Sherlund (2009), Agarwal, Ambrose, Chomsisengphet, and Sanders (2010), Bajari, Chu, and Park (2010), Barlevy and Fisher (2010), Berndt, Hollifield, and Sandas (2010), Campbell, Giglio, and Pathak (2010), Corbae and Quintin (2010), Demyanyk and Hemert (2010), Gabriel and Rosenthal (2010), Gerardi, Rosen, and Willen (2010), Glaeser, Gottleb, and Gyourko (2010), Goetzmann, Peng, and Yen (2010), Jiang, Nelson, and Vytlacil (2010a), Li, White, and Zhu (2010), Piskorski, Seru, and Vig (2010), Purnanandam (2010), Rajan, Seru, and Vig (2010), Woodward and Hall (2010), and An, Deng, and Gabriel (2011).

The remainder of this paper is structured as follows. Section 2 describes our data sources and reports summary statistics. In Section 3 we study the mortgage choice of households and describe the main features of mortgage contracts. In Section 4 we study the delinquency of different contract types. Section 5 offers concluding remarks.

## 2 Data Sources and Summary Statistics

This section describes in detail the data sources and differences of the main mortgage contracts offered in the United States over the last decade.

#### 2.1 Data

Our study relies on several complementary data sources that cover various aspects of the housing market during the period between 2003 and 2009. In particular, the micro level analysis of mortgage contract choice and performance relies heavily on the proprietary mortgage-level database offered by Lender Processing Services (LPS) Applied Analytics (formerly known as McDash Analytics). LPS collects data from some of the nation's largest mortgage servicers that report contract and borrower details at the time of loan origination, as well as monthly information on mortgage performance. The LPS data coverage has grown steadily over time, with 9 out of 10 largest servicers reporting to the database by 2003. Our database covers about 10 million mortgages with a total loan value of more than \$2 trillion originated between 2003 and 2007. We track the performance of all loans till the end of 2009.

For the purposes of our study, the availability of granular information on mortgage contract terms is of particular importance. For each of the loans, LPS provides information on the loan interest rate, the amortization schedule, and the securitization status. For adjustable rate mortgages (ARMs), we know the rate at origination, the frequency of resets, the reference rate, and the associated contractual spread. For loans that do not amortize steadily over their term, we know the horizon of the interest-only period, whether negative amortization

is allowed and if so, to what extent and over what period of time. This information allows us to precisely categorize loan contracts. The LPS data also contains key information on borrower and property characteristics at the time of origination. These include the appraised property value, the loan-to-value ratio (LTV), property type (single family or condominium), whether the property was to be occupied by the borrower, and the borrower's creditworthiness as measured by their FICO (Fair Isaac Corporation) credit score.<sup>3</sup>

An important feature of the LPS database is that unlike some other data sources, it is not limited to a particular subset of the loan universe. The LPS data cover prime, subprime, and Alt-A loans,<sup>4</sup> and include loans that are privately securitized, those that are sold to Government Sponsored Enterprises (GSEs), and loans that are held on banks' balance sheets. Even though this allows for a broad set of mortgage contracts, the coverage is somewhat skewed in favor of securitized loans that are more likely to be serviced by large corporations reporting to LPS. Still, the large overall size of the dataset ensures that we have ample coverage of all contract types.

We complement borrower information in LPS with household income data collected under the Home Mortgage Disclosure Act (HMDA). Doing so allows us to compute some of the key measures of loan affordability, such as the ratio of house value to income (VTI). We further augment the loan-level data with information on trends in local home prices. Quarterly data on home prices is available by metropolitan statistical area (MSA) from the Federal Housing Finance Agency (FHFA)-an independent federal agency that is the successor to the Office of

<sup>&</sup>lt;sup>3</sup>As Bajari, Chu, and Park (2010) emphasize, an important feature of the FICO score is that it measures a borrower's creditworthiness prior to taking out the mortgage. FICO scores range between 300 and 850 Typically, a FICO score above 800 is considered very good, while a score below 620 is considered subprime. As reported on the Fair Isaac Corporation website (www.myfico.com), borrowers with FICO scores above 760 are able to take out 30-year fixed rate mortgages at interest rates that are 160 basis points lower, on average, than those available for borrowers with scores in the 620-639 range.

<sup>&</sup>lt;sup>4</sup>Alt-A loans are a middle category of loans, more risky than prime and less risky than subprime. They are generally made to borrowers with good credit scores, but the loans have characteristics that make them ineligible to be sold to the GSEs-for example, limited documentation of the income or assets of the borrower or higher loan-to-value ratios than those specified by GSE limits.

Federal Housing Enterprise Oversight (OFHEO) and other government entities.<sup>5</sup> We use the all-transactions FHFA House Price Index (HPI) that is based on repeat sales and refinancing information. We use the index to construct borrower-specific variables on cumulative growth in local house prices. At the more aggregate level, we utilize zip code level information from the 2000 U.S. Census to control for broad demographic characteristics, such as education levels and age distributions. We also make use of the annual per capita income level and unemployment rate data at the MSA level from the Bureau of Economic Analysis (BEA).

To determine whether lender recourse has an impact on mortgage choices and mortgage defaults we follow Ghent and Kudlyak (2010) and classify U.S. states into recourse and non-recourse categories. Whereas lender claims in non-recourse states are limited to the value of the collateral securing the loan, lenders in recourse states may be able to collect on debt not covered by the proceedings from a foreclosure sale by obtaining a deficiency judgment.<sup>6</sup>

The summary statistics on these variables are presented in Table 1 and we will discuss differences in these variables across mortgage types in more detail in Section 2.3. All of the variables discussed above are described in Table 12.

## 2.2 Mortgage Contract Design

The menu of household mortgage choices was dominated for decades by fully-amortizing longterm fixed rate mortgages (FRM) and, to a lesser extent, by adjustable rate mortgages (ARM) that locked in the initial interest rate for the first five to seven years of the contract. From

<sup>&</sup>lt;sup>5</sup>As part of the Housing and Economic Recovery Act of 2008 (HERA), the Federal Housing Finance Regulatory Reform Act of 2008 established a single regulator, the FHFA, for GSEs involved in the home mortgage market, namely, Fannie Mae, Freddie Mac, and the 12 Federal Home Loan Banks. The FHFA was formed by a merger of the Office of Federal Housing Enterprise Oversight (OFHEO), the Federal Housing Finance Board (FHFB), and the U.S. Department of Housing and Urban Development's government-sponsored enterprise mission team (see www.fhfa.gov for additional details).

<sup>&</sup>lt;sup>6</sup>Ghent and Kudlyak (2010) classify the following states as non-recourse: Alaska, Arizona, California, Iowa, Minnesota, Montana, North Dakota, Oregon, Washington, and Wisconsin. There is some ambiguity with respect to the recourse status of California loans. Refinance loans in California are subject to recourse only if the lender chooses to pursue judicial foreclosure. Although we observe whether a loan is used for new purchase or refinancing, we cannot assess the credibility of the threat of lender recourse through judicial foreclosure. In this paper, only new purchase loans in California are defined as non-recourse. The results are robust to categorizing all California loans as non-recourse.

the vantage point of the borrower, FRM contracts preserve contract terms established at origination for the lifetime of the loan. For practical purposes, the same can be said of ARM contracts with a relatively long fixed-rate period, given the average borrower tenure at a particular house of about seven years. Knowing the monthly servicing costs and amortization schedules simplifies the household budgeting problem. Over the last decade, complex mortgages (CM) that allow for the deferral of principal repayment have become increasingly popular. They typically featured zero or negative amortization, short interest rate reset periods, and very low introductory teaser interest rates. The vast majority of CM also exhibit adjustable interest rates.

In this section we illustrate the different payment patterns of some popular U.S. mortgage contracts. We classify all mortgage products into three groups: (1) Fixed Rate Mortgages (FRM); (2) Adjustable Rate Mortgages (ARM); and (3) Complex Mortgages (CM).

Fixed rate mortgages are level-payment fully-amortizing loans with maturities between 15 and 30 years. For example, a 30-year \$500,000 fixed rate mortgage with a 5% interest rate requires equal monthly payments of \$2,684 for 360 months, at which point it is paid off completely. Borrowers generally have the option to prepay the mortgage if they sell the property or if they refinance their loan due to a decrease in mortgage interest rates.

Adjustable rate mortgages are fully-amortizing loans where the interest rate changes after an initial period according to a preselected interest rate index. These mortgages exhibit caps and floors that prevent interest rates from changing too much over the lifetime of the loan. ARM interest rates are generally lower than those on FRMs due to the increasing term structure of interest rates and the availability of the prepayment option in FRMs.<sup>7</sup> For example, a 30-year 5/1 ARM for \$500,000 with a 4.5% initial interest rate has initial

<sup>&</sup>lt;sup>7</sup>Fixed rate mortgages can be refinanced when interest rates decrease, which is a very valuable option that is priced in the initial interest rate. There are numerous papers on prepayments. See for example, Dunn and McConnell (1981), Schwartz and Torous (1989), Stanton (1995), Dunn and Spatt (1999), Deng, Quigley, and Gabriel (2000), Longstaff (2005), Campbell (2006), Gabaix, Krishnamurthy, and Vigneron (2007), and Schwartz (2007).

mortgage payments of \$2,533 per month for the first 60 months. Subsequently, the payments can increase or decrease depending on the level of interest rates. If the interest rate rises to 7%, the monthly payment in the sixth year increases to \$3,221.8

Complex mortgages include a variety of back-loaded mortgage contracts. Most complex mortgages feature adjustable interest rates and exhibit time-varying amortization schedules. The most popular contract is an Interest Only (IO) mortgage that only requires borrowers to pay the mortgage interest over an initial time period lasting typically between five and ten years. Subsequently, the mortgage becomes a fully-amortizing loan. For example, a 5-year IO adjustable rate loan with a 30-year maturity, a \$500,000 initial balance, and a 4.5% initial interest rate has initial mortgage payments of \$1,875 per month for the first 60 months. Subsequently, the payments reset according to the future interest rates. If the interest rate increases to 7%, then the monthly payment in the sixth year will almost double to \$3,534, as the loan also begins to amortize. Even if interest rates remain at 4.5%, the mortgage payment will increase to \$2,779 per month at the end of the initial interest-only period. The payments increase even more for mortgages with longer interest-only periods.

The other popular type of a complex mortgage is a Negative Amortization Mortgage (NEGAM), also known as Option ARMs. These mortgages give borrowers the option to initially pay even less than the interest due. The difference between the interest due and the actual mortgage payment is added to the loan balance. These mortgages carry the risk of larger increases in mortgage payments, when the mortgage is recast to become a fully amortizing loan after 5-10 years or when the loan balance exceeds the initial balance at origination by more than a certain amount (typically 10-25%). An additional common feature of NEGAM is a low teaser interest rate of between 1-2% during the first 1-12 months. The minimum payment on a NEGAM contract is often set at the level sufficient to cover teaser interest rate

<sup>&</sup>lt;sup>8</sup>Several papers study the tradeoff between FRMs and ARMs (e.g., Campbell and Cocco (2003), Vickery (2007), and Koijen, Van Hemert, and Van Nieuwerburgh (2009)).

charges, and is raised by up to 7.5% on each anniversary of the loan.<sup>9</sup>

### 2.3 Summary Statistics by Mortgage Type

Table 2 reports statistics for our broad mortgage categories – fully-amortizing fixed rate, fully-amortizing adjustable rate, and complex mortgage types. Complex mortgages are further separated into interest only and negative amortization loans. Our data contain in excess of 10 million loan contracts originated between 2003 and 2007. In our sample, 70% of mortgages are fixed rate mortgages, 13% are adjustable rate mortgages, and the remaining 17% are complex mortgages.

Complex mortgages, on average, are associated with higher loan amounts relative to the traditional ARM and FRM mortgages, and are used to finance more expensive houses. For example, the average home value for complex loans is \$471,754, whereas the average home values for FRMs and ARMs are \$264,189 and \$307,238, respectively.

Counter to some of the commonly made assertions about complex mortgages, complex mortgages are extended to borrowers with high income levels and prime credit scores. Indeed, households that take out complex mortgages report significantly higher annual incomes (\$133,581) than households borrowing through fixed rate (\$87,835) or adjustable rates mortgages (\$99,816). This difference persists even when the sample is restricted to loans underwritten on the basis of fully documented income. Panel A of Figure 2 summarizes the cumulative distribution function of income levels of FRM, ARM, and CM borrowers. The income distribution for CM borrowers lies well to the right of the distribution of borrowers using fully amortizing ARM and FRM contracts. We also find that CM borrowers have credit scores

<sup>&</sup>lt;sup>9</sup>There are several possible reasons why complex mortgages became more popular in the early 2000s. First, borrowers and lenders might have increased their real estate appreciation expectations during the period of the housing price bubble. Second, the low interest rate environment of the early 2000s appears to improve the attractiveness of low amortization instruments for borrowers. For example, the monthly mortgage payment on a 30-year FRM with an initial balance of \$500,000 is \$2,108 using a 3% interest rate. The initial payment on a corresponding IO mortgage is 40.7% lower (\$1,250 vs. \$2,108). On the other hand, the initial mortgage payment is only 9.1% lower for an IO mortgage compared to a FRM (\$3,333 vs. \$3,669) at an 8% interest rate.

that are better than ARM borrowers and similar to those of FRM borrowers. Whereas 24% of ARM borrowers have FICO credit scores below 620, the same can be said of only 10% of FRM and only 6% of CM borrowers. Panel B of Figure 2 summarizes the distribution of FICO scores for different mortgage contracts. These results emphasize that the clientele for complex mortgages differs significantly from that for subprime loans.

Nevertheless, the average ratio of house value to income (VTI)—an inverse measure of affordability—is considerably higher in complex mortgage contracts, suggesting that CM borrowers are purchasing more expensive houses relative to their income. Panel C of Figure 2 indicates that CM borrowers tend to have substantially higher VTI ratios than both ARM and FRM borrowers. Median households using FRMs, ARMs, and CMs have value-to-income ratios of 3.0, 3.1, and 3.8, respectively. Thus, for a given level of income CM borrowers purchase houses valued at about 20% more, likely aided by the lower initial payments on their mortgage contracts. Yet, higher spending on houses is not reflected in the loan-to-value (LTV) ratios, as all mortgage types have similar first lien LTV values.<sup>10</sup>

Several other loan characteristics are different for complex mortgages. CM borrowers are more likely to live in a condominium and are slightly more likely to use the property they are financing for investment purposes. We also find significant differences in the frequency of prepayment penalties across mortgage types. Unlike FRMs, a significant fraction of ARMs and CMs face penalties if the loans are prepaid within the first two or three years. Complex mortgages have a slightly higher share of refinancings compared to new purchases.

Since complex loans are particularly popular for expensive homes, they are also more likely to exceed the conforming loan limit (i.e. be jumbo loans). Hence, although 79% of FRMs are securitized by government-sponsored enterprises (GSEs, such as Fannie Mae, Freddie Mac, amd Ginnie Mae), only 26% of CMs go through the GSEs. Private securitization partially

<sup>&</sup>lt;sup>10</sup>LPS data is collected at the loan and not property level, which limits one's ability to construct an accurate estimate of the total debt secured by the house. In particular, we are unable to account for second-lien mortgages loans (the so-called "piggyback loans") used to finance the house.

offsets the lack of GSE involvement in the ARM and CM markets.

Complex mortgage borrowers receive significantly lower initial interest rates than FRM or ARM borrowers. The mean initial interest rate on complex mortgages of 5.04% is significantly lower than the rates on FRMs (6.16%) and ARMs (6.17%). This result is primarily caused by negative amortization mortgages that charge, on average, an initial teaser interest rate of only 1.86%. For each ARM and CM loan we impute the rate such borrowers might have received had they chosen a conventional 30-year fixed rate mortgage instead. We define such hypothetical rate as the average interest rate on all 30 year FRMs originated in the same month, state, with similar loan size, LTV ratio, and FICO score. The hypothetical FRM interest rate is similar across the various contracts.

Unfortunately, we do not observe the age and the education level of borrowers directly. However, we can compute the proportion of people in zip codes between 20 and 40 years and the proportion of adults with a college education. We find that CM borrowers tend to live in cities with higher education levels.

From a spatial standpoint, complex mortgages are more common in geographic areas that experienced high house price appreciation. The average 5-year cumulative price appreciation among complex borrowers amounted to 74%, as compared with 50% among traditional FRM borrowers. Finally, the population growth rate and the unemployment rate at the time of origination, which capture macroeconomic conditions at the MSA level, are similar in areas with different mortgage compositions.

Complex mortgages are more likely to be non-recourse, where the lender cannot access assets of the defaulting households beyond the value of the collateral securing the loan. Whereas only 16% of FRMs are non-recourse, 27% of CMs are non-recourse.

The last two columns of Table 2 break out the key summary characteristics among the two complex mortgage types. Negative amortization loans, on average, appear to be used to finance more expensive homes and are associated with higher loan values. They also display

the highest VTI ratios. As expected, negative amortization loans with their low teaser interest rates commonly carry prepayment penalties. Finally, IO contracts appear to have been subject to stricter underwriting criteria. Whereas only 20% of IOs were underwritten on the basis of less than full documentation, 43% of NEGAM loans were issued in this manner.

### 2.4 Affordability of Different Mortgage Contracts

Complex mortgage products initially have relatively low payments that enable the purchase of more expensive homes. Figure 3 depicts the ratio of the monthly payments on ARMs and CMs relative to hypothetical FRM loans of the same amount. The terms of such FRMs are derived from loans originated in the same month and state for borrowers with similar FICO scores and loan-to-value ratios. We observe that during the first year the majority of ARMs and CMs have lower payments; for the majority of CMs (52.3%) payments are at least 20% lower. Panels B and C show that payments remain lower for the vast majority of surviving CMs even three or five years after origination. Thus, a relatively small fraction of complex mortgages have substantial payment resets that could not be managed by refinancing into a new contract. This indicates that CM borrowers continued to have relatively low payments throughout the mortgage crisis of 2007-2009.

An alternative way to illustrate the evolution of payments is to compare payments over time to those realized during the first year. Figure 4 shows the majority of CMs do not experience significant jumps in payments during the first five years. In fact, monthly payments rise by more than 20% only for 11.6% (26.2%) of CM borrowers after three (five) years.

By virtue of their amortization structure, complex loans largely maintain a high leverage ratio over time. Figure 5 depicts the distribution of the remaining mortgage balance one, three, and five years after origination relative to the original balance. Even after five years (Panel C), less than 20% of surviving complex mortgages paid down more than 5% of their initial balance, while about 14% increased their balance by 5% or more. This creates a sharp

contrast with FRM and ARM borrowers who gradually pay down their loans. This dynamic deterioration in relative leverage ratios becomes particularly dramatic in the event of slower house price appreciation, as experienced during the housing crisis of 2007-2009.<sup>11</sup>

## 3 Mortgage Choice

In this section, we analyze the characteristics of mortgage borrowers more systematically, relating to the hypotheses outlined in the Introduction. To recall, complex mortgages may be: (i) an appealing contract for lenders because they allow to obfuscate terms to naive households; (ii) an optimal contract for borrowers expecting income growth and house price appreciation; and (iii) a contract that attracts a self-selected set of borrowers that seek to make a concentrated bet on housing and that are aware of the value of the default option. We realize that contract choice reflects the decisions of both borrowers and lenders, with the latter determining the menu of available contract options and possibly also steering them towards certain items on that menu. Throughout the analysis, we will attempt to differentiate between supply- and demand-side determinants, but we'll employ "choice" for ease of exposition.

## 3.1 Multinomial Logit Regressions of Contract Choice

We estimate the likelihood of selection of a particular mortgage contract type (ARM or CM) relative to a baseline contract, which we take to be an FRM. These relative likelihoods are estimated as a function of loan- and borrower-level covariates, as well as MSA-level aggregates. Formally, we use maximum likelihood to estimate the following multinomial logit regressions:

$$\frac{Prob(Y_i = m)}{Prob(Y_i = FRM)} = e^{\beta_m X_i + FE_i^{Time} + FE_i^{State} + FE_i^{Lender} + \epsilon_i},$$
(1)

<sup>&</sup>lt;sup>11</sup>The higher long-term loan-to-value ratios of complex loans may have contributed to a further deterioration in housing markets, as suggested by the leverage effect of Stein (1995) and Lamont and Stein (1999). Additional papers that study the macro-economic aspects of housing prices include Lustig and Van Nieuwerburgh (2005), Ortalo-Magne and Rady (2006), Piazzesi, Schneider, and Tuzel (2007), Brunnermeier and Julliard (2008), Landvoigt, Piazzesi, and Schneider (2010), and Van Nieuwerburgh and Weill (2010).

where  $Prob(Y_i = m)/Prob(Y_i = FRM)$  is the probability of obtaining an ARM or CM relative to a FRM, X is a vector of mortgage-specific covariates,  $FE^{Time}$  are indicator variables for the origination quarters,  $FE^{State}$  are state indicator variables, and  $FE^{Lender}$  are lender-specific indicator variables. To facilitate the interpretation of the economic significance of the results, we standardize the continuous variables by subtracting their mean and dividing by their standard deviation.

Table 3 reports the estimated coefficients. All regressions include time fixed effects and the standard errors are clustered by MSA. Since some of the MSA level variables are not available for the full sample, the corresponding specifications include fewer observations than the overall sample summarized in Table 2. In addition, for computational reasons we only include the largest 50 lenders in the specification with lender fixed effects.

We find little support for the first hypothesis that complex mortgages are pushed to naive households by predatory lenders, in which case we should expect these loans to be concentrated in low income areas with poorly educated households. Instead, we find that households with higher income levels are significantly more likely to obtain a complex mortgage than to take out a more traditional FRM loan. The log of the probability of a given outcome relative to the base case is a linear function of the covariates in equation (1). Thus, the coefficients have a direct interpretation as the marginal effect of X on the log of the probability ratio. Put differently, the exponentiated value of a coefficient is the change in the relative probability of outcome m for a unit change in the corresponding variable. Following this interpretation, a one standard deviation change in log income raises the likelihood of choosing a CM over an FRM contract almost twofold (exp(0.64)=1.90).

While it is possible that the positive association between CM contract choice and income reflects the propensity of CMs to be concentrated in high income MSAs, specifications that incorporate MSA-level controls and state fixed effects preserve these relationships. Therefore, even within individual geographies, complex mortgage choice is favored by the relatively

well-off. These state fixed effects also control for other unobserved state-specific differences in regulation, topography, and geography. The coefficient on income also remains highly statistically significant if we include lender fixed effects. These lender fixed effects control for the fact that some lenders might offer only specific mortgage instruments and might target specific clienteles.

Moreover, households with higher FICO scores are substantially more likely to choose a CM than to choose an ARM, although the results are mixed when we compare the propensity to choose a CM relative to a FRM.<sup>12</sup> Areas with higher proportions of college graduates and with higher median incomes are also associated with a higher proportion of CM contracts. Overall, there is little evidence that a typical complex mortgage is taken out by poor and naive households that are more prone to predatory lending. These results are consistent with the survey evidence of Cox, Brounen, and Neuteboom (2011), who find that Dutch households with lower financial literary and with higher risk aversion are less likely to select mortgages with deferred amortization schedules.

We find some evidence consistent with the second hypothesis of complex mortgages being "affordability products" for households that anticipate income or house price growth. The estimated coefficients on the loan-to-value (LTV) and the value-to-income (VTI) ratios are significantly higher for CM households, suggesting that these households are stretching their budget to afford more expensive homes. While we do not observe household expectations for their income and house price growth, we introduce several proxies for these expectations. Since young households anticipate a higher growth rate of their labor income than older households, we use the proportion of adults between 20 and 40 years to proxy for income expectations and find that CM contracts are more popular in areas with a larger portion of younger households. To the extent that households extrapolate past local experiences to build their expectations

<sup>&</sup>lt;sup>12</sup>The coefficient on the FICO score variable is significantly positive for CM if we select ARMs as the baseline group or if we run a simple logit regression.

about future house price dynamics, we use the prior five years' house price appreciation in the MSA to proxy for the expected future house price growth. Borrowers in geographic areas where appreciation was substantial might be more willing to accept non-amortizing loans if they expect the appreciation to continue in the future. In addition, the prior one-year population growth rate in the MSA captures the migration pressure. Geographic areas with significant population growth might be areas where households expect significant house price and income growth. We find that past house price appreciation and the local population growth significantly increase the propensity of obtaining a CM. This evidence suggests that the expectations of continued house price and income growth are likely a driving force behind the popularity of complex mortgages. Another piece of evidence consistent with the idea of CM contracts as affordability product is that they are much more prevalent for mortgages above the GSE conforming loan limit. Such mortgages cannot be securitized by the GSEs and, consequently, result in somewhat higher interest rates (the so-called jumbo spread). This increases the relative appeal of payment-shrinking CM products.

Finally, we also find supporting evidence for the third hypothesis that complex mortgages are selected by a different type of households who might be less averse to strategic default. In particular, we observe that CM borrowers are much more likely to provide incomplete documentation for their loans. The greater reliance of CM contracts on low-documentation underwriting is consistent with borrowers' effort to inflate their income to qualify for a higher loan amount needed for an expensive house. To the extent that these households are willing to hide or manipulate their income information in the loan application process, it is possible that their decision to pay back debt is influenced solely by economic considerations and not some contractually unspecified ethical norms.

In addition, we find that CM mortgages are also more likely to be used to finance condominiums and investment properties. Owners of these properties have potentially lower costs of strategically defaulting on their properties. They might therefore have an incentive to pay down their mortgage balance relatively slowly to increase the option value of strategic default.

Moreover, obtaining a non-recourse mortgage raises the likelihood of a complex mortgage over a fixed-rate contract nearly twofold. This might be caused by the higher option value of defaulting on non-recourse mortgages, when a delinquent household can simply walk away without worrying about lenders accessing their other assets.

In summary, we find that CM borrowers are well-educated high-income households with prime credit scores. They are stretching their budget to purchase expensive houses, partly due to their expectation of higher future income or house price growth. They are also different from the more traditional mortgage borrowers in that they might be more receptive to the idea of strategic default.

#### 3.2 Robustness Tests

Table 4 reports the coefficients of multinomial logit regressions that further differentiate between the two main types of complex contracts. The estimates are consistent with the univariate results in Table 2. In particular, we see that NEGAM contracts are used by high-income borrowers to refinance their high-priced primary residences, often on the basis of only limited income and asset documentation. It is likely that such refinancings are serial in nature, which further underscores the fragility of such contracts in environments where the refinancing markets freeze up.

Our conclusion that borrowers of complex mortgages are relatively financially sophisticated is partially based on the fact that these borrowers report higher income levels. However, the income levels of low-documentation borrowers are not verified and might not be reliable. To investigate whether this biases our results, Table 5 presents the CM coefficients of the multinomial logit regressions for the sample of households with full documentation loans.<sup>13</sup>

<sup>&</sup>lt;sup>13</sup>About half of our observations have a missing "Low Documentation" variable. Our base case results in Table 3 include these households, setting the "Low Documentation" value to zero. Thus, Table 5 includes only the households for which we know explicitly that they submitted fully documented loan applications.

Overall, conditioning on full documentation loans has no qualitative effect on our main results.

Table 5 also shows that our results remain materially unaffected if we only study purchase transactions or investment properties. Since our database might undersample portfolio loans, we also report the results of the 10% of loans that are not securitized. The coefficient on income increases in this specification, whereas the coefficients on the other variables are not affected much. Finally, we exclude all mortgages originated in the state of California, which accounts for around 15% of our observations but a greater proportion of the CM loans. Whereas most coefficients remain stable in this specification, the non-recourse mortgage coefficient decreases somewhat, but remains economically and statistically significant.

In unreported robustness tests we run a separate multinomial logit model for each year and document that the determinants of mortgage choice are relatively stable over time. For example, the income level is positively related to the choice of complex mortgages for each year in our sample.

## 4 Mortgage Delinquencies

In this section we study the delinquency outcomes of different types of mortgages. A mortgage is considered delinquent if the borrower is at least 60 days late with the payment.

## 4.1 Reasons for Mortgage Delinquencies

The existing literature differentiates between two types of delinquencies: (i) "cash flow defaults" that occur because of unfavorable income shocks or changes in required loan payment and (ii) "strategic defaults" that reflect optimal borrower exercise of the default option.

Since the required payment on CM contracts may change due to both interest rate and amortization schedule resets, they may subject the borrower to greater hazard of cash flow defaults. On the other hand, the initial low mortgage payments may lessen this hazard during the early years of the loan. The same can be said of the contracts (e.g., Option ARMs) that

give borrowers the flexibility to adjust their payments as their income flows fluctuate.

The fact that CM borrowers have higher loan-to-value ratios for any given path of house prices (Figure 5) also makes them more likely to enter the strategic default state, the necessary condition for which is negative home equity. The higher embedded equity of an ARM or FRM borrower makes it more likely that they will continue making payments in the case of a house price shock or sell their home in the case of financial difficulties, relative to a CM borrower that is more likely to choose to walk away from their loan.

Finally, as we have shown in the previous section, borrowers that choose CM contacts might have other unobservable characteristics that make them more prone to default relative to traditional mortgage holders. For example, these households might be more risk seeking, have more volatile income streams, or be more financially sophisticated and thus more receptive to the idea of strategic default.

Our empirical strategy will be to control to the greatest extent possible for measures associated with cash flow shocks and the value of the default option and check whether the remaining differences in delinquencies (if any) may be attributed to self-selection of sophisticated households into CM contracts.

## 4.2 Summary of Mortgage Delinquency

Figure 6 plots the distribution of mortgage delinquencies by contract type during the first five years after origination. In each month we depict the proportion of remaining mortgages that become delinquent for the first time. We observe that complex mortgages have strictly higher delinquency rates than fixed rate mortgages at all horizons. Mortgage delinquencies of complex loans reach peaks of 1.2% of surviving loans 27 and 39 months after origination. These peaks occur three months after common reset intervals, since delinquency begins when a mortgage payment is at least 60 days late. We observe a similar peak for ARMs at the 27-month horizon. The same information cumulated over time is presented in Panel A of

Table 6 that reports the proportion of mortgages that are delinquent after 1, 3, and 5 years.

Panel B of Table 6 shows the proportion of households with different mortgage types that declare bankruptcy. We observe that FRMs have the lowest bankruptcy rate at all horizons. Households borrowing using CMs have higher bankruptcy rates than ARMs at a five year horizon. Thus, personal bankruptcies are significantly less likely than mortgage delinquencies. Panel C indicates that CM borrowers have intermediate propensities to prepay their mortgages compare to FRM and ARM borrowers.

Whereas ARMs have slightly higher rates of delinquency at short horizons, CMs have substantially higher rates at longer horizons. It must be kept in mind that borrowers of complex loans have relatively high delinquency propensities despite having higher credit scores than ARM borrowers, as summarized in Table 2. It is also insightful that the delinquency rate increases substantially even before the minimum loan payments are reset after two or three years, indicating that some borrowers of complex loans do not even make the relatively low initial mortgage payments.

### 4.3 Hazard Model of Delinquency

To investigate the determinants of mortgage delinquencies, we run the following Cox proportional hazard model:

$$h(i,t) = h_0(t;s,v)e^{\beta X_{i,t} + FE_t^{Year} + \epsilon},$$
(2)

where the hazard rate h(t) is the estimated probability of first time 60-day delinquency at time t conditional on surviving to time  $t_-$ ,  $h_0(t)$  is the baseline hazard rate, X is a vector of household-specific covariates, and  $FE_t^{Year}$  is an indicator variable for the calendar year to control for different vintage effects and macroeconomic conditions. We allow the baseline hazard to vary for each combination of the origination year v and the state s or for each combination of the origination year v and the lender  $s.^{14}$  The loan sample is expanded to a loan-year level so that time-varying covariates can be included. Also, time is scaled so that the first observation date is the calendar year of origination (time 0), and subsequent calendar years are measured relative to the year of origination. Implicitly, loans of different vintages are compared with each other, so that the baseline hazard represents the probability of delinquency for a borrower with covariates of 0 at t years after origination. In some specifications we separate complex mortgages into the two sub-types (IO and NEGAM). The continuous covariates are again standardized by subtracting the mean and dividing by the standard deviation. The last specification replaces the year-state baseline with the year-lender baseline to control for lender-specific determinants of delinquency.

Table 7 reports the estimated coefficients of the propensity of first time delinquency. In the first column, we use only borrower and loan characteristics at origination to estimate the delinquency hazards. In the second column, we include area-specific variables and timevarying characteristics. The third column incorporates controls for loan ownership to explore the impact of securitization.

Our key finding is that CMs have significantly higher delinquency rates than FRMs in all specifications, notwithstanding a wide array of control variables. The effect is both economically and statistically significant. For example, in column 1, the coefficient of 0.736 for CM implies that the probability of delinquency for a borrower with a complex mortgage relative to that for a similar borrower with a fixed rate mortgage is  $e^{1\times0.736}/e^{0\times0.736} = 2.1$ . Stated differently, the complex borrower is about twice as likely to be delinquent as a fixed rate borrower, holding all other characteristics fixed. This impact of having a complex mortgage on mortgage delinquency is similar to a one-standard deviation decrease in the FICO credit score, which is generally perceived to be a strong predictor of mortgage delinquency.

<sup>&</sup>lt;sup>14</sup>The results are not affected significantly if we use a common baseline hazard, origination year-specific baselines, or origination year and state-specific baselines.

The first set of additional explanatory variables in column 2 is related to cash flow defaults. Of particular interest is the variable "Payment Resets," defined as the increase in the minimum required mortgage payment since origination. By construction, this variable is zero for FRMs. Recall that payment resets are driven only by interest rate changes for ARMs and by both interest rate and amortization changes for CMs. Consequently, CMs have larger resets than ARMs, as illustrated by the CDFs of payments over time in Figure 4. Although we find that payment resets increase the hazard rate of delinquency, the economic magnitude of the effect is small. This, too, is consistent with the finding in Figure 4 that a relatively small fraction of CMs experience significant payment resets. These small increases can be attributed to a general downward trend in interest rates over our sample period, as well as to the ability of CM borrowers to refinance loans prior to amortization resets. In sum, these results suggest a rather limited role for contract-driven cash flow shocks in explaining higher CM delinquency rates.

Other variables related to cash flow defaults include the income level and the FICO score, which partly reflect households' financial conditions. Higher income and higher FICO households are less constrained and are indeed found to have lower delinquency rates. To gauge the impact of local macro-economic conditions on mortgage delinquency, we include the unemployment level, defined as the proportion of unemployed in an MSA, and the income growth rate, defined as the growth rate of the mean income level at the MSA level since the mortgage was originated. The estimated coefficients on both variables are intuitive. Higher unemployment levels and lower income growth rates lead to more delinquencies, suggesting that general cash flow difficulties in meeting cash flow payments contribute to mortgage delinquency.

The second set of explanatory variables is related to strategic default, defined as the choice to default on a mortgage when the house value is low relative to the remaining loan balance even if the borrower has the means to make mortgage payments. Proxies of leverage ratios are the most obvious candidates for explaining strategic default. Since households can always

sell their house and pay off their mortgage in full when the remaining loan balance is low relative to the current house value, it is not surprising that higher LTV ratios at origination are associated with higher delinquency hazards. In Section 3.1 we argued that borrowers with low or no documentation loans and owners of investment properties might be more willing to default strategically. Indeed, our results confirm that these variables significantly increase the delinquency rate.

The dynamic evolution of house values and loan balances is more germane to our attempt to isolate contract-specific covariates of default. In particular, the lack of mandatory amortization for complex mortgages should translate directly into higher loan balances over the loan's lifetime (as illustrated in Figure 5). Consequently, we introduce a time-varying measure of change in the loan balance since origination. To further account for fluctuations in household leverage, we add an estimate of the change in the home value since origination as proxied by the mean MSA-level house price appreciation since the origination of the specific loan. Our results in column 2 suggest that both factors contribute to mortgage delinquencies. However, house price declines play a significantly stronger economic role in explaining delinquencies than the deferral of loan amortization common in CM contracts. Notably, the inclusion of all these controls for cash flow or strategic defaults preserve the independent effect of contract choice, as the coefficient on the CM dummy remains practically unchanged.

Finally, in column 3, we control for whether the mortgage was securitized by Government Sponsored Entities or by private parties. Since the impact of securitization has obtained significant attention in the literature, we want to ensure that the impact of complex loans is not subsumed by the lenders' propensity to securitize. We find that complex mortgages are still associated with higher delinquency hazards after controlling for government and private securitization. Thus, the role of mortgage contract design is distinct from the well-documented impact of securitization.

The first three specifications of Table 7 use state-year baseline hazards and already control

for state and time specific determinants of delinquency.<sup>15</sup> The last specification uses lenderyear baseline hazards, which accounts for the possibility that mortgages originated by different lenders might exhibit different delinquency rates over time because individual lenders might attract a particular borrower type that might focus on specific mortgage contracts. Complex mortgages exhibit higher delinquency rates under all specifications.<sup>16</sup>

The fact that CMs have significantly higher delinquency rates subject to a multitude of controls suggests that CM borrowers are fundamentally different from FRM borrowers. They might be more risk seeking in general, as revealed by their choices for CM contracts. They might have riskier income or might be more receptive to the idea of strategic default. These results are consistent with the structural model of Corbae and Quintin (2010), who find that the presence of nontraditional mortgages amplified the severity of the mortgage crisis.

### 4.4 Delinquency and Financial Sophistication

Complex mortgages can be originated to households with different levels of financial sophistication. The predatory lending hypothesis postulates that complex mortgages are sold to unsophisticated investors that do not understand the detailed contract specifications. This hypothesis suggests that delinquencies are particularly likely for unsophisticated borrowers using complex mortgages. On the other hand, for sophisticated CM borrowers delinquencies could be higher if these borrowers have higher propensities to default strategically.

Since we do not have any direct household-level measures of financial sophistication, we use two proxies: the households' income level and the FICO score. Borrowers with higher income levels tend to be more financially sophisticated. Furthermore, households that can maintain a high FICO score show that they have the discipline and knowledge to plan their

<sup>&</sup>lt;sup>15</sup>The results are not affected qualitatively if we use MSA-year baseline hazards instead.

<sup>&</sup>lt;sup>16</sup>In unreported regressions, we also restricted the sample to CM and ARM mortgages issued to prime borrowers. Doing so eliminates FRM and subprime borrowers that may be fundamentally different from complex mortgage borrowers on some unobserved risk tolerance or behavioral characteristics. The results still suggest considerably higher conditional delinquency rates for CMs.

financial matters effectively. In addition, since the sensitivity of the delinquency rate to the LTV ratio captures households' tendency to strategically default on their mortgages, we use the default sensitivity to LTV as a measure of sophistication. If complex borrowers are more receptive to the idea of strategic default, then we expect a stronger default sensitivity to the loan-to-value ratio for complex mortgages.

Table 8 introduces interaction effects between complex mortgages and the income level, the FICO credit score, and the LTV ratio to our baseline hazard model. Consistent with the sophisticated borrower hypothesis, we find positive interaction effects in all these cases. This holds true whether interactions are estimated one-by-one (columns 1-3) or jointly (column 4). The estimate of  $\gamma$  in column 2 suggests that the improvement in the hazard rate from a one standard deviation increase in the FICO score is about 6% lower for a CM mortgage than for an FRM mortgage.<sup>17</sup>

Table 8 shows that while CM borrowers on average default more than traditional mortgage borrowers, the difference in the delinquency rates for complex and traditional borrowers is particularly high for households with higher income levels and with higher FICO credit scores. Moreover, the delinquency rate of complex borrowers is particularly sensitive to measures of strategic default like the LTV ratio. Together, this evidence suggests that strategic default considerations play an important role in explaining the high delinquency rates of complex mortgages during the recent mortgage crisis.

<sup>&</sup>lt;sup>17</sup>The interpretation of interaction effects in non-linear models is subject to the well-known critique of Ai and Norton (2003). However, we make use of the specific functional form of the Cox proportional hazard model to argue that the reported coefficients have a direct and natural interpretation. To see this, let's consider the example of the interaction term between the FICO score and the CM indicator. Taking logs of the hazard function and then differentiating with respect to FICO yields  $\partial \log h(i,t)/\partial FICO = \beta_{FICO} + \gamma \times CM$ . Since CM is a binary variable,  $\gamma$  shows the difference in relative changes in the hazard function in response to changes in the FICO score for different types of mortgages.

### 4.5 Personal Bankruptcy vs. Mortgage Delinquency

The decision to default on a mortgage is related to the decision to declare bankruptcy. Contrasting the determinants of personal bankruptcy with the determinants of mortgage delinquency gives us important insights about the motivation of the delinquency behavior. It is not necessary that households that default on their mortgages are also declaring bankruptcy. Nor is it necessary that households that declare bankruptcy default on their mortgages. For example, in our sample only 13% of households that are delinquent on their mortgage also declare bankruptcy.<sup>18</sup>

Table 9 reports the propensity of households to declare personal bankruptcy. Not surprisingly, most coefficients have the same signs as in the delinquency regression of Table 7. For example, higher income and higher FICO scores reduce the propensities of both mortgage delinquency and bankruptcy. It is interesting that some variables show up with different signs in the two regressions. For example, although households with investment properties have significantly higher mortgage delinquency rates, they are not more likely to file for personal bankruptcy. This evidence suggests that owners of investment properties are more likely to walk away from the property when it is economical to do so, even if they can afford to continue the mortgage payment. Similarly, loans with low documentation are also more likely to be delinquent but do not have higher bankruptcy rates.

To capture other complex mortgage borrowers that might also be more strategic in their default decisions, we include an interaction effect between complex mortgages and prior mortgage delinquency. Whereas households with prior mortgage delinquencies are substantially more likely to declare personal bankruptcy, we observe that this effect is significantly reduced for borrowers with complex loans. That is, conditional on delinquency, complex borrowers exhibit a smaller increase in the probability of declaring bankruptcy than traditional borrowers

 $<sup>^{18}\</sup>mathrm{See}$  Li, White, and Zhu (2010) for a discussion of the relationship between bankruptcy laws and mortgage defaults.

after being delinquent on their mortgage.<sup>19</sup> This result suggests that borrowers of complex mortgages are less likely to be delinquent due to adverse cash flow shocks, which would affect both mortgage delinquency and personal bankruptcy. Instead, they are more likely to strategically default on their mortgages when it is optimal to do so, for example, when the value of the house as a going concern is lower than the remaining mortgage balance.

#### 4.6 Additional Robustness Tests

Whereas interest-only mortgages keep a stable loan-to-value ratio over the first three to five years of the loan, negative amortization loans allow households to increase their debt level during the first years after the loan origination. Thus one should expect a magnification effect for the more extreme negative amortization contracts. Table 10 separates IO and NEGAM loans and indicates that the coefficients for negative amortization loans are generally larger in magnitude than for the more conservative IO loans. For example, an IO mortgage has twice as high a propensity to be delinquent than a FRM. On the other hand, a NEGAM has about 2.4 times higher propensity to default than a FRM.

Table 11 shows that CM borrowers exhibit higher delinquency rates than borrowers of FRM for the subsamples of full documentation loans, for purchase transactions, for investment properties, for non-securitized loans, and for loans not originated in California.

In addition, we also run the hazard models separately for each annual origination cohort. The coefficients on complex loans are significantly positive for each individual origination cohort between 2003 and 2007. Furthermore, the remaining coefficients are generally consistent over the different cohorts.

<sup>&</sup>lt;sup>19</sup>Since both of the interacted variables (CM and Delinquency) are binary, it is more natural to compute the associated marginal effect and statistical significance using the approach outlined in Li, White, and Zhu (2010). In a nutshell, we compute differences in predicted effects of the onset of delinquency on bankruptcy for CM and non-CM loans using the full estimated model, with other control variables at their sample means. The associated standard errors are computed using the delta method. The test confirms that the estimated interaction effect is strongly negative and statistically significant.

## 5 Conclusions

The recent housing crisis brought the extension of credit to subprime borrowers and agency problems inherent in mortgage securitization to the forefront of academic research. This paper focuses on a different aspect of credit markets during this time – namely, the proliferation of non-amortizing mortgages. In addition to variable interest rates, such mortgages also feature changes in amortization schedules set off by a variety of triggers. These complex mortgage contracts became very popular during the mid-2000s and vanished almost completely after the housing crisis of 2007-2009.

We find that complex mortgages are the contract of choice for high credit quality and high income households, in contrast to the low income population targeted by subprime mortgages. These households use complex mortgages as affordability products to purchase houses that are expensive relative to their incomes, partly due to their expectations of higher future income and house price growth. Complex mortgage borrowers might also be more receptive to the idea of strategic default than traditional mortgage borrowers since they are more likely to provide incomplete documentation for their loans, to be owners of investment properties, and to reside in non-recourse states in which lenders do not have access to non-collateralized assets in the event of mortgage delinquency.

Consistent with the notion that households who self select into complex mortgage products are fundamentally different from traditional mortgage borrowers, we find that complex mortgages experienced substantially higher defaults, controlling for a variety of borrower and loan characteristics, as well as macroeconomic shocks. Higher delinquency rates cannot be attributed solely to greater leverage of complex mortgages and the onset of amortization resets brought about by inability to refinance complex loans. Furthermore, the difference in the delinquency rates between complex and traditional borrowers increases with both measures of financial sophistication (like income or credit scores) and measures of strategic default (like the LTV ratio). Conditional on being delinquent on their mortgages, complex borrowers are less likely to file for bankruptcy than traditional borrowers. These results suggest that complex mortgage borrowers are more strategic in their default decisions than other types of mortgage borrowers and shed doubt on the hypothesis that complex mortgages are pushed by predatory lenders to naive households who do not fully understand the mortgage terms.

## References

- Adelino, M., K. Gerardi, and P. Willen (2009). Why don't lenders renegotiate more home mortgages? Redefaults, self-cures, and securitization. NBER Working Paper 15159.
- Agarwal, S., B. W. Ambrose, S. Chomsisengphet, and A. B. Sanders (2010). Thy neighbor's mortgage: Does living in a subprime neighborhood affect one's probability of default? Forthcoming: *Real Estate Economics*.
- Ai, C. and E. C. Norton (2003). Interaction terms in logit and probit models. *Economics Letters* 80, 123–129.
- Amromin, G., J. Huang, and C. Sialm (2007). The tradeoff between mortgage prepayments and tax-deferred savings. *Journal of Public Economics 91*, 2014–2040.
- An, X., Y. Deng, and S. A. Gabriel (2011). Asymmetric information, adverse selection, and the pricing of CMBS. *Journal of Financial Economics* 100, 304–325.
- Bajari, P., C. S. Chu, and M. Park (2010). An empirical model of subprime mortgage default from 2000 to 2007. University of Minnesota and Federal Reserve Board.
- Barlevy, G. and J. Fisher (2010). Backloaded mortgages and house price speculation. Federal Reserve Bank of Chicago.
- Berndt, A., B. Hollifield, and P. Sandas (2010). The role of mortgage brokers in the subprime crisis. Carnegie Mellon University.
- Bond, P., D. K. Musto, and B. Yilmaz (2009). Predatory mortgage lending. *Journal of Financial Economics* 94, 412–427.
- Brunnermeier, M. K. and C. Julliard (2008). Money illusion and housing frenzies. *Review of Financial Studies* 21, 135–180.
- Campbell, J. Y. (2006). Household finance. Journal of Finance 61, 1553–1604.
- Campbell, J. Y. and J. F. Cocco (2003). Household risk management adn optimal mortgage choice. *Quarterly Journal of Economics* 118, 1449–1494.
- Campbell, J. Y., S. Giglio, and P. Pathak (2010). Forced sales and house prices. Forthcoming: *American Economic Review*.
- Carlin, B. I. (2009). Strategic price complexity in retail financial markets. *Journal of Financial Economics* 91, 278–287.
- Carlin, B. I. and G. Manso (2010). Obfuscation, learning, and the evolution of investor sophistication. University of California Los Angeles and MIT.
- Cocco, J. F. (2010). Understanding the trade-offs of alternative mortgage products. London Business School.
- Corbae, D. and E. Quintin (2010). Mortgage innnovation and the foreclosure boom. University of Texas and University of Wisconsin.
- Cox, R., D. Brounen, and P. Neuteboom (2011). Mortgage choice by households; Empirical evidence from the mortgage market. RSM Erasmus University Rotterdam and Tilburg University.
- Demyanyk, Y. and O. V. Hemert (2010). Understanding the subprime mortgage crisis. Forthcoming: Review of Financial Studies.
- Deng, Y. and J. M. Quigley (2009). Irrational borrowers and the pricing of residential mortgages. National University of Singapore and University of California Berkeley.
- Deng, Y., J. M. Quigley, and S. A. Gabriel (2000). Mortgage terminations, heterogeneity and the exercise of mortgage options. *Econometrica* 68, 275–307.

- Dunn, K. B. and J. J. McConnell (1981). Valuation of mortgage-backed securities. *Journal of Finance* 36, 599–617.
- Dunn, K. B. and C. S. Spatt (1999). Call options, points, and dominance restrictions on debt contracts. *Journal of Finance* 54, 2317–2337.
- Gabaix, X., A. Krishnamurthy, and O. Vigneron (2007). Limits of arbitrage: Theory and evidence from the mortgage backed securities market. *Journal of Finance* 62, 557–596.
- Gabaix, X. and D. Laibson (2006). Shrouded attributes, consumer myopia, and information suppression in competitive markets. *Quarterly Journal of Economics* 121, 461–504.
- Gabriel, S. A. and S. S. Rosenthal (2010). Do the GSEs expand the supply of mortgage credit? New evidence of crowd out in the secondary mortgage market. Forthcoming: *Journal of Public Economics*.
- Gerardi, K. S., H. S. Rosen, and P. S. Willen (2010). The impact of deregulation and financial innovation on consumers: The case of the mortgage market. *Journal of Finance* 65, 333–360.
- Ghent, A. C. and M. Kudlyak (2010). Recourse and residential mortgage default: Theory and evidence from U.S. states. Baruch College and Federal Reserve Bank of Richmond.
- Glaeser, E. L., J. Gottleb, and J. Gyourko (2010). Can cheap credit explain the housing boom? Harvard University.
- Goetzmann, W. N., L. Peng, and J. Yen (2010). The subprime crisis and house price appreciation. Yale University and University of Colorado.
- Guiso, L., P. Sapienza, and L. Zingales (2009). Moral and social constraints to strategic default on mortgages. European University Institute, Northwestern University, and University of Chicago.
- Jiang, W., A. A. Nelson, and E. Vytlacil (2010a). Liar's loan? Effects of origination channel and information falsification on mortgage delinquency. Columbia University.
- Jiang, W., A. A. Nelson, and E. Vytlacil (2010b). Securitization and loan performance: A contrast of ex ante and ex post relations in the mortgage market. Columbia University.
- Keys, B. J., T. Mukherjee, A. Seru, and V. Vig (2009). Financial regulation and securitization: Evidence from subprime loans. *Journal of Monetary Economics* 56, 700–720.
- Keys, B. J., T. Mukherjee, A. Seru, and V. Vig (2010). Did securitization lead to lax screeing? evidence from subprime loans. *Quarterly Journal of Economics* 125, 307–362.
- Koijen, R. S. J., O. Van Hemert, and S. Van Nieuwerburgh (2009). Mortgage timing. *Journal of Financial Economics* 93, 292–324.
- Lamont, O. and J. C. Stein (1999). Leverage and house-price dynamics in U.S. cities. *RAND Journal of Economics* 30, 498–514.
- Landvoigt, T., M. Piazzesi, and M. Schneider (2010). The housing market(s) of san diego. Stanford University.
- Li, W., M. J. White, and N. Zhu (2010). Did bankruptcy reform cause mortgage default to rise? Forthcoming: American Economic Journal: Economic Policy.
- Longstaff, F. A. (2005). Borrower credit and the valuation of mortgage-backed securities. *Real Estate Economics* 33, 619–661.
- Loutskina, E. and P. E. Strahan (2009). Securitization and the declining impact of bank financial condition on loan supply: Evidence from mortgage originations. *Journal of Finance* 64, 861–922.
- Lustig, H. and S. Van Nieuwerburgh (2005). Housing collateral, consumption insurance and risk premia: An empirical perspective. *Journal of Finance* 60, 1167–1219.

- Mayer, C., K. Pence, and S. Sherlund (2009). The rise in mortgage defaults. *Journal of Economic Perspectives 23*, 23–50.
- Mian, A. and A. Sufi (2009). The consequences of mortgage credit expansion: Evidence from the U.S. mortgage default crisis. *Quarterly Journal of Economics* 124, 1449–1496.
- Ortalo-Magne, F. and S. Rady (2006). Housing market dynamics: On the contribution of income shocks and credit constraints. *Review of Economic Studies* 73, 459–485.
- Piazzesi, M., M. Schneider, and S. Tuzel (2007). Housing, consumption, and asset pricing. Journal of Financial Economics 83, 531–569.
- Piskorski, T., A. Seru, and V. Vig (2010). Securitization and distressed loan renegotiation: Evidence from the subprime mortgage crisis. Forthcoming: *Journal of Financial Economics*.
- Piskorski, T. and A. Tchistyi (2010). Optimal mortgage design. Review of Financial Studies 23, 3098–3140.
- Purnanandam, A. (2010). Originate-to-distribute model and subprime mortgage crisis. University of Michigan.
- Rajan, U., A. Seru, and V. Vig (2010). The failure of models that predict failure: Distance, incentives and defaults. University of Michigan, University of Chicago, and London Business School.
- Schwartz, A. (2007). Household refinancing behavior in fixed rate mortgages. Harvard University.
- Schwartz, E. S. and W. N. Torous (1989). Prepayment and the valuation of mortgage-backed securities. *Journal of Finance* 44, 375–392.
- Stango, V. and J. Zinman (2011). Fuzzy math, disclosure regulation, and credit market outcomes: Evidence from truth-in-lending reform. Review of Financial Studies 24, 506–534.
- Stanton, R. (1995). Rational prepayment and the valuation of mortgage-backed securities. Review of Financial Studies 8, 677–708.
- Stein, J. C. (1995). Prices and trading volume in the housing market: A model with down-payment effects. *Quarterly Journal of Economics* 110, 379–406.
- Van Nieuwerburgh, S. and P.-O. Weill (2010). Why has house price dispersion gone up? Review of Economic Studies 77, 1567–1606.
- Vickery, J. (2007). Interest rates and consumer choice in the residential mortgage market. Federal Reserve Bank of New York.
- Woodward, S. E. and R. E. Hall (2010). Diagnosing consumer confusion and sub-optimal shopping effort: Theory and mortgage-market evidence. NBER Working Paper 16007.

Table 1: Summary Statistics
This table reports means, standard deviations, medians, and first and third quartiles for our data sample.

	Mean	Std. Dev.	1st Quart.	Median	3rd Quart.
Loan Amount	210,944	150,387	108,431	168,000	267,500
House Value	305,969	252,661	144,900	232,000	385,000
Income	97,359	81,844	50,000	75,000	115,000
Income with Full Documentation	91,975	78,548	48,000	71,000	108,000
FICO	707	67	662	715	762
FICO less than 620	0.11	0.32	0.00	0.00	0.00
First Lien Loan to Value (LTV)	0.74	0.18	0.67	0.79	0.82
Value to Income (VTI)	3.60	2.34	2.22	3.18	4.42
Initial Interest Rate (in %)	5.97	1.39	5.50	6.00	6.50
Hypothetical FRM Interest Rate (in %)	6.19	0.45	5.88	6.13	6.50
Refinance	0.41	0.49	0.00	0.00	1.00
Condo	0.13	0.34	0.00	0.00	0.00
Investment Property	0.10	0.30	0.00	0.00	0.00
Low Documentation	0.14	0.34	0.00	0.00	0.00
Government Securitized	0.65	0.48	0.00	1.00	1.00
Private Securitized	0.25	0.43	0.00	0.00	1.00
With Prepayment Penalty	0.13	0.34	0.00	0.00	0.00
Above Conforming Limit	0.11	0.31	0.00	0.00	0.00
MSA Level Variables					
BEA Income	37,710	8,194	32,085	$36,\!538$	42,349
College or More	0.34	0.16	0.22	0.32	0.44
Young	0.40	0.09	0.35	0.40	0.45
House Price Change Prior 5 Years	0.55	0.33	0.26	0.49	0.78
Population Growth (in %)	1.10	1.44	0.29	0.82	1.74
Unemployment Rate (in %)	5.01	1.39	4.10	4.80	5.70
Non-Recourse Mortgage	0.18	0.39	0.00	0.00	0.00
Number of Observations	10,135,601				

Table 2: Summary Statistics by Mortgage Type
This table reports summary statistics for Fixed Rate Mortgages (FRM), Adjustable Rate Mortgages (ARM), Complex Mortgages (CM), and for different types of complex mortgages including Interest-Only Mortgages (IO) and Negative Amortization Mortgages (NEGAM).

	All Mortgages			Complex 1	Mortgages
	FRM	ARM	CM	IO	NEGAM
Loan Amount	178,534	221,526	332,598	326,831	353,446
House Value	264,189	307,238	471,754	462,870	503,870
Income	87,835	99,816	133,581	131,172	142,290
Income with Full Documentation	85,302	$95,\!572$	117,895	117,194	121,300
FICO	710	681	713	715	707
FICO less than 620	0.10	0.24	0.06	0.07	0.04
First Lien Loan to Value (LTV)	0.74	0.77	0.73	0.74	0.72
Value to Income (VTI)	3.47	3.52	4.15	4.13	4.22
Initial Interest Rate (in %)	6.16	6.17	5.04	5.92	1.86
Hypothetical FRM Interest Rate (in %)	6.17	6.21	6.23	6.25	6.15
Refinance	0.41	0.35	0.45	0.40	0.64
Condo	0.11	0.16	0.19	0.19	0.15
Investment Property	0.09	0.10	0.12	0.12	0.11
Low Documentation	0.11	0.12	0.25	0.20	0.43
Government Securitized	0.79	0.40	0.26	0.31	0.06
Private Securitized	0.15	0.42	0.53	0.52	0.57
With Prepayment Penalty	0.06	0.27	0.33	0.19	0.81
Above Conforming Limit	0.05	0.14	0.33	0.31	0.39
MSA Level Variables					
BEA Income	36,918	37,483	40,953	41,004	40,767
College or More	0.33	0.36	0.38	0.39	0.38
Young	0.40	0.41	0.41	0.41	0.40
House Price Change Prior 5 Years	0.50	0.56	0.74	0.72	0.82
Population Growth (in %)	1.10	1.11	1.10	1.14	0.96
Unemployment Rate (in %)	5.03	5.20	4.79	4.75	4.97
Non-Recourse Mortgage	0.16	0.21	0.27	0.28	0.25
Number of Observations	7,077,626	1,284,132	1,773,843	1,389,488	384,355

Table 3: Multinomial Logit Regressions

This table reports the coefficients of multinomial logit regressions for Fixed Rate Mortgages (FRM), Adjustable Rate Mortgages (ARM), and Complex Mortgages (CM). The coefficients are measured relative to FRM. The significance levels are abbreviated with asterisks: One and two asterisks denote significance at the 5 and 1% level, respectively.

	Individu Covar		MSA-Covar		Sta Fixed I		Lend Fixed I	
	ARM	CM	ARM	CM	ARM	CM	ARM	CM
Log(Income)	0.33**	0.64**	0.22**	0.48**	0.22**	0.44**	0.26**	0.47**
8()	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
FICO	-0.52**	-0.04**	-0.51**	$-0.02^{*}$	$-0.52^{**}$	-0.04**	$-0.40^{**}$	0.04**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LTV	0.20**	0.32**	0.21**	0.34**	0.21**	0.35**	0.33**	0.44**
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.01)	(0.03)
VTI	0.30**	0.54**	0.19**	0.35**	0.15**	0.28**	0.26**	0.40**
	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)
Low Documentation	$0.09^{*}$	0.78**	$0.14^{**}$	0.82**	0.14**	0.82**	0.16**	0.60**
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
Above Loan Limit	0.71**	1.28**	0.66**	$1.17^{**}$	0.70**	1.13**	0.55**	1.11**
	(0.06)	(0.08)	(0.05)	(0.06)	(0.04)	(0.04)	(0.05)	(0.07)
Condo	0.59**	0.70**	0.42**	0.46**	0.39**	0.42**	0.49**	0.52**
	(0.05)	(0.06)	(0.05)	(0.05)	(0.03)	(0.02)	(0.05)	(0.04)
Investment Property	0.29**	0.21**	0.35**	0.21**	0.33**	0.17**	0.28**	0.31**
	(0.03)	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Refinance	-0.26**	0.22**	-0.22**	0.29**	-0.30**	$0.09^{*}$	-0.19**	0.02
	(0.02)	(0.03)	(0.02)	(0.05)	(0.02)	(0.04)	(0.02)	(0.05)
College or More			0.11**	0.04*	0.12**	0.05**	0.14**	0.09**
			(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Young			0.09**	0.10**	0.09**	0.06**	0.07**	0.08**
			(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
House Price Change			0.08**	0.36**	0.15**	0.28**	0.02	0.30**
			(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Population Growth			0.02	0.12**	0.03	$0.07^{**}$	0.03	0.14**
			(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.04)
Log(BEA Income)			0.10**	0.15**	0.14**	0.23**	0.09**	0.14**
			(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.04)
Non-Recourse States			0.34**	0.63**			0.24**	0.49**
			(0.05)	(0.08)			(0.06)	(0.08)
Year Dummies	Ye		Ye	s	Ye	<u></u>	Ye	s
State Dummies	No		No		Ye		No	
Lender Dummies	N		No		N		Ye	
Observations	10,135	5,601	8,914	,795	8,914	.,795	6,719	,987

Table 4: Multinomial Logit Regressions for Detailed Classification
This table reports the coefficients of multinomial logit regressions for Fixed Rate Mortgages (FRM),
Adjustable Rate Mortgages (ARM), Interest-Only Mortgages (IO), and Negative Amortization Mortgages (NEGAM). The coefficients are measured relative to FRM. The significance levels are abbre-

viated with asterisks: One and two asterisks denote significance at the 5 and 1% level, respectively.

	Indiv	idual-level Co	variates	MS	A-level Cova	riates
•	ARM	IO	NEGAM	ARM	IO	NEGAM
Log(Income)	0.33**	0.59**	0.86**	0.23**	0.43**	0.72**
- ,	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
FICO	-0.52**	-0.03**	-0.09**	-0.51**	-0.02	-0.04**
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
LTV	0.20**	0.28**	0.50**	0.21**	0.30**	0.56**
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
VTI	0.30**	0.53**	0.61**	0.19**	0.34**	0.40**
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
Low Documentation	0.11**	0.53**	1.60**	0.16**	0.57**	1.64**
	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
Above Loan Limit	0.71**	1.27**	1.26**	0.66**	1.18**	1.10**
	(0.06)	(0.08)	(0.10)	(0.05)	(0.06)	(0.07)
Condo	0.59**	0.73**	0.59**	0.42**	0.49**	0.34**
	(0.05)	(0.06)	(0.09)	(0.05)	(0.04)	(0.07)
Investment Property	0.29**	0.20**	0.33**	0.36**	0.19**	$0.35^{**}$
	(0.03)	(0.05)	(0.06)	(0.02)	(0.03)	(0.04)
Refinance	-0.25**	0.02	1.07**	-0.21**	0.08	1.21**
	(0.02)	(0.03)	(0.05)	(0.02)	(0.04)	(0.06)
College or More				0.11**	0.06**	$-0.07^{**}$
				(0.01)	(0.02)	(0.02)
Young				0.09**	0.10**	0.07**
				(0.02)	(0.02)	(0.02)
House Price Change				0.08**	0.32**	0.56**
				(0.03)	(0.04)	(0.05)
Population Growth				0.02	0.13**	0.07
				(0.03)	(0.04)	(0.05)
Log(BEA Income)				0.10**	0.14**	0.19**
				(0.03)	(0.04)	(0.07)
Non-Recourse States				0.34**	0.60**	0.83**
				(0.05)	(0.08)	(0.11)
Year Dummies		Yes			Yes	
State Dummies		No			No	
Lender Dummies		No			No	
Observations		10,135,601			8,914,795	

Table 5: Multinomial Logit Regressions for Subsamples

This table reports the coefficients of multinomial logit regressions for the following subsamples: loans with full documentation; loans originated to purchase a new house; loans used to finance an investment property; non-securitized loans; and loans originated in states other than California. The coefficients are measured relative to FRM. The significance levels are abbreviated with asterisks: One and two asterisks denote significance at the 5 and 1% level, respectively.

	Full	Purchases	Investment	Not	Exclude
	Documentation	Only	Property	Securitized	California
Log(Income)	0.42**	0.43**	0.41**	0.70**	0.46**
,	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
FICO	$-0.15^{**}$	$-0.09^{**}$	$-0.10^{**}$	$-0.09^{**}$	$-0.02^{'}$
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
LTV	$0.37^{**}$	0.16**	0.43**	0.38**	0.25**
	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)
VTI	0.34**	0.34**	$0.35^{**}$	0.42**	0.36**
	(0.02)	(0.02)	(0.04)	(0.04)	(0.03)
Low Documentation	,	0.58**	$-0.15^{**}$	2.14**	0.67**
		(0.05)	(0.03)	(0.13)	(0.05)
Above Loan Limit	1.06**	1.18**	0.97**	0.73**	1.03**
	(0.06)	(0.07)	(0.05)	(0.07)	(0.04)
Condo	0.45**	0.46**	0.17**	0.35**	0.44**
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Investment Property	$0.04^{'}$	0.29**	,	0.03	0.29**
1	(0.03)	(0.03)		(0.04)	(0.03)
Refinance	0.09*	,	0.03	0.42**	0.25**
	(0.04)		(0.03)	(0.06)	(0.04)
College or More	$0.05^{*}$	$0.04^{*}$	0.06**	0.06**	0.07**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Young	0.09**	0.12**	0.07**	0.04*	0.08**
Ü	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
House Price Change	0.22**	0.44**	0.37**	0.31**	0.28**
· ·	(0.03)	(0.04)	(0.03)	(0.05)	(0.06)
Population Growth	0.13**	0.17**	0.17**	$0.05^{'}$	0.18**
	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
Log(BEA Income)	0.11**	0.18**	0.12**	0.02	0.14**
,	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Non-Recourse States	0.63**	0.71**	0.45**	0.86**	0.36**
	(0.06)	(0.10)	(0.06)	(0.10)	(0.11)
Origination Voor Duranica	Yes	Yes	Yes	Yes	Yes
Origination Year Dummies					
State Dummies	No No	No No	No No	No No	No No
Lender Dummies		No			
Observations	3,279,098	5,214,519	826,569	929,429	7,545,202

Table 6: Mortgage Delinquencies and Household Bankruptcies
This table reports the proportion of mortgages that are at least 60 days delinquent, the proportion
of households with mortgages that declare bankruptcy, and the proportion of mortgages that are
prepaid after one, three, and five years. Mortgages are prepaid if a borrower refinances the loan or
pays back the loan completely before maturity.

Panel A: Proportion of Mortgages that are Delinquent						
	FRM	ARM	CM			
1 Year	2.62	6.57	3.77			
3 Years	9.43	16.30	17.42			
5 Years	12.66	19.50	24.06			
Number of Loans	7,077,626	$1,\!284,\!132$	1,773,843			

Panel B: Proportion of Households Declaring Bankruptcy							
	FRM ARM CM						
1 Year	0.25	0.53	0.25				
3 Years	1.52	2.38	2.19				
5 Years	2.16	3.05	3.20				
Number of Loans	7,077,626	1,284,132	1,773,843				

Panel C: Proportion of Mortgages that are Prepaid							
	FRM	ARM	CM				
1 Year	7.39	15.10	11.09				
3 Years	28.30	46.95	36.94				
5 Years	38.86	59.47	45.12				
Number of Loans	7,077,626	1,284,132	1,773,843				

Table 7: Hazard Model of Mortgage Delinquency
This table reports the estimates from a Cox proportional hazard model for mortgage delinquency.
The significance levels are abbreviated with asterisks: One and two asterisks denote significance at the 5 and 1% level, respectively.

	Individual-level	MSA-Level	Securitization	Lender-Year
	Covariates	Covariates	Controls	Baselines
CM	0.74**	0.71**	0.54**	$0.67^{**}$
	(0.01)	(0.01)	(0.01)	(0.01)
ARM	0.48**	0.49**	0.32**	0.43**
	(0.01)	(0.01)	(0.01)	(0.01)
Log(Income)	-0.13**	$-0.07^{**}$	-0.08**	$-0.05^{**}$
,	(0.01)	(0.01)	(0.01)	(0.01)
FICO	$-0.67^{**}$	$-0.66^{**}$	$-0.64^{**}$	$-0.63^{**}$
	(0.01)	(0.01)	(0.01)	(0.01)
LTV	0.52**	0.49**	0.51**	0.47**
	(0.01)	(0.01)	(0.01)	(0.01)
VTI	0.04**	0.05**	0.05**	0.06**
V 11	(0.01)	(0.01)	(0.01)	(0.01)
Low Documentation	0.03*	0.04**	0.09**	0.007
Low Bocumentation	(0.01)	(0.01)	(0.01)	(0.01)
Above Loan Limit	0.22**	$0.32^{**}$	0.14**	0.33**
Above Loan Limit	(0.03)	(0.02)	(0.02)	(0.02)
Condo	$-0.16^{**}$	-0.08**	$-0.07^{**}$	-0.01
Condo				
I	(0.03)	(0.03)	(0.02)	(0.03)
Investment Property	0.39**	0.36**	0.32**	0.33**
D. C	(0.03)	(0.03)	(0.03)	(0.03)
Refinance	0.09**	0.04**	0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
College or More		-0.21**	-0.21**	-0.21**
		(0.01)	(0.01)	(0.01)
Young		$0.02^{*}$	$0.02^{*}$	-0.01
		(0.01)	(0.01)	(0.01)
Log(BEA Income)		0.05**	$0.05^{**}$	$0.04^{*}$
		(0.02)	(0.02)	(0.02)
Increase in House Value		-0.43**	-0.43**	-0.47**
		(0.02)	(0.02)	(0.02)
Increase in Loan Balance		0.04**	0.04**	0.06**
		(0.01)	(0.01)	(0.01)
Payment Resets		0.03**	0.03**	0.03**
		(0.00)	(0.00)	(0.00)
Unemployment Rate		$0.02^{'}$	$0.02^{'}$	0.03
e nempley mem 10000		(0.01)	(0.01)	(0.02)
Income Growth since Origination		-0.16**	$-0.15^{**}$	-0.15**
meome growin since origination		(0.02)	(0.02)	(0.04)
Government Securitized		(0.02)	-0.21**	(0.04)
Government Decurrenceu			(0.02)	
Private Securitized			0.26**	
i iivate securitized				
			(0.01)	
State-Year Baselines	Yes	Yes	Yes	No
Lender-Year Baselines	No	No	No	Yes
Observations	32,590,515	25,619,647	25,619,647	25,619,718

Table 8: Hazard Model of Mortgage Delinquency with Interaction Effects
This table reports the estimates from a Cox proportional hazard model for mortgage delinquency,
with interaction effects that capture the sensitivity of complex mortgage delinquencies to other loan
and household characteristics. The significance levels are abbreviated with asterisks: One and two
asterisks denote significance at the 5 and 1% level, respectively.

CM	0.70**	0.75**	0.67**	0.69**
	(0.01)	(0.01)	(0.01)	(0.01)
$CM \times Log(Income)$	0.08**			0.08**
	(0.01)			(0.01)
$CM \times FICO$		0.06**		0.06**
		(0.01)		(0.01)
$CM \times LTV$			0.10**	0.13**
			(0.02)	(0.02)
ARM	$0.49^{**}$	0.48**	0.49**	0.49**
	(0.01)	(0.01)	(0.01)	(0.01)
Log(Income)	-0.10**	-0.07**	-0.07**	-0.09**
	(0.01)	(0.01)	(0.01)	(0.01)
FICO	-0.66**	-0.68**	-0.66**	-0.68**
	(0.01)	(0.01)	(0.01)	(0.01)
LTV	0.50**	0.49**	0.48**	0.47**
	(0.01)	(0.01)	(0.01)	(0.01)
VTI	0.05**	0.05**	0.05**	0.05**
	(0.01)	(0.01)	(0.01)	(0.01)
Low Documentation	0.03**	0.03**	0.04**	0.04**
	(0.01)	(0.01)	(0.01)	(0.01)
Above Loan Limit	0.28**	$0.31^{**}$	$0.32^{**}$	0.28**
	(0.02)	(0.02)	(0.02)	(0.02)
Condo	-0.08**	-0.08**	-0.08**	-0.08**
	(0.03)	(0.03)	(0.03)	(0.03)
Investment Property	0.36**	0.36**	0.36**	0.36**
	(0.03)	(0.03)	(0.03)	(0.03)
Refinance	0.04**	0.04**	0.04**	0.04**
	(0.01)	(0.01)	(0.01)	(0.01)
College or More	-0.21**	-0.21**	-0.21**	-0.21**
	(0.01)	(0.01)	(0.01)	(0.01)
Young	$0.02^{**}$	$0.02^{**}$	$0.02^{*}$	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
Log(BEA Income)	0.05**	0.04*	0.05**	0.04**
	(0.02)	(0.02)	(0.02)	(0.02)
Increase in House Value	-0.43**	-0.43**	-0.43**	-0.43**
	(0.02)	(0.02)	(0.02)	(0.02)
Increase in Loan Balance	0.03**	0.04**	0.04**	0.04**
	(0.01)	(0.01)	(0.01)	(0.01)
Payment Resets	0.03**	0.03**	0.03**	0.03**
	(0.00)	(0.00)	(0.00)	(0.00)
Unemployment Rate	$0.02^{'}$	$0.02^{'}$	$0.02^{'}$	$0.02^{'}$
	(0.01)	(0.01)	(0.01)	(0.01)
Income Growth since Origination	-0.16**	-0.16**	-0.16**	-0.16**
	(0.03)	(0.03)	(0.02)	(0.02)
	` /	, ,	, ,	` /
Observations	25,619,647	25,619,647	25,619,647	25,619,647
	-0,010,011	-0,010,011	-0,010,011	-0,010,011

Table 9: **Hazard Models of Personal Bankruptcy**This table reports the estimates from a Cox proportional hazard model for personal bankruptcy. The significance levels are abbreviated with asterisks: One and two asterisks denote significance at the 5 and 1% level, respectively.

CM	0.65**	0.62**	0.48**	0.62**
	(0.01)	(0.01)	(0.01)	(0.02)
Delinquency			1.30**	$1.37^{**}$
			(0.03)	(0.03)
CM x Delinquency				-0.28**
				(0.04)
ARM	0.32**	0.34**	0.32**	0.32**
	(0.01)	(0.02)	(0.02)	(0.02)
Log(Income)	$-0.17^{**}$	-0.11**	-0.10**	-0.10**
	(0.01)	(0.01)	(0.01)	(0.01)
FICO	$-0.47^{**}$	-0.46**	-0.37**	-0.37**
	(0.01)	(0.01)	(0.01)	(0.01)
LTV	0.58**	$0.55^{**}$	$0.45^{**}$	$0.45^{**}$
	(0.01)	(0.01)	(0.01)	(0.01)
VTI	-0.22**	-0.19**	-0.24**	-0.24**
	(0.02)	(0.02)	(0.02)	(0.02)
Low Documentation	0.00	0.01	0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Above Loan Limit	0.20**	0.30**	0.26**	0.26**
	(0.03)	(0.03)	(0.03)	(0.03)
Condo	-0.29**	-0.14**	-0.15**	-0.15**
	(0.03)	(0.02)	(0.02)	(0.02)
Investment Property	0.05	0.01	-0.10**	-0.10**
	(0.02)	(0.02)	(0.02)	(0.02)
Refinance	0.41**	0.37**	0.34**	0.34**
	(0.01)	(0.01)	(0.01)	(0.01)
College or More		-0.21**	-0.16**	-0.16**
		(0.01)	(0.01)	(0.01)
Young		-0.06**	$-0.07^{**}$	-0.07**
- (, -		(0.01)	(0.01)	(0.01)
Log(BEA Income)		-0.02	-0.04*	-0.04*
		(0.02)	(0.02)	(0.02)
Increase in House Value		-0.35**	-0.31**	-0.31**
		(0.02)	(0.02)	(0.02)
Increase in Loan Balance		0.10**	0.10**	0.10**
		(0.01)	(0.01)	(0.01)
Payment Resets		-0.00	$-0.01^*$	$-0.01^*$
TT 1		(0.00)	(0.00)	(0.00)
Unemployment Rate		-0.03	-0.03	-0.03
		(0.02)	(0.02)	(0.02)
Income Growth since Origination		-0.18**	-0.15**	-0.15**
		(0.03)	(0.03)	(0.03)
01	04.050.000	00 550 400	00 550 400	00 550 400
Observations	$34,\!252,\!339$	26,778,403	26,778,403	26,778,403

Table 10: Hazard Model of Mortgage Delinquency for Detailed Classification This table reports the estimates from a Cox proportional hazard model for mortgage delinquency for different types of complex loans including IO and NEGAM. The significance levels are abbreviated with asterisks: One and two asterisks denote significance at the 5 and 1% level, respectively.

asterisks. One and two asterisk					
IO	0.68**	0.68**	0.71**	0.64**	0.66**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
NEGAM	0.89**	0.83**	0.99**	0.83**	0.86**
TO T (T	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$IO \times Log(Income)$		0.06**			0.06**
NECANA I (I		(0.01)			(0.01)
$NEGAM \times Log(Income)$		0.13**			0.13**
TO DIGO		(0.01)	0.04**		(0.01)
IO x FICO			0.04**		0.04**
NECAM FIGO			(0.01)		(0.01)
NEGAM x FICO			0.21**		0.20**
IO ITW			(0.01)	0.00**	(0.01)
IO x LTV				0.09**	0.11**
NEGAM x LTV				(0.02) $0.22**$	$(0.02) \\ 0.25**$
NEGAWI X LI V					
ARM	0.49**	0.50**	0.49**	(0.02) $0.49**$	(0.02) $0.49**$
ARM				(0.49)	
Log(Ingomo)	(0.01) $-0.08**$	(0.01) $-0.10**$	(0.01) $-0.08**$	-0.08**	(0.01) $-0.09**$
Log(Income)	(0.01)	(0.01)	-0.03 $(0.01)$	(0.01)	(0.01)
FICO	-0.66**	-0.66**	-0.68**	$-0.67^{**}$	-0.68**
1100	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LTV	0.49**	0.50**	0.49**	0.47**	$0.47^{**}$
LIV	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
VTI	0.05**	0.05**	0.05**	0.05**	0.05**
V 11	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Low Documentation	0.03*	0.02	0.02	0.03**	0.03**
Low Documentation	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Above Loan Limit	0.31**	0.28**	0.30**	0.31**	0.27**
TIDOVO EGGII EIIIIIV	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Condo	-0.08**	-0.08**	-0.08**	-0.08**	-0.08**
Oshqo	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Investment Property	0.36**	0.36**	0.36**	0.36**	0.35**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Refinance	$0.03^{*}$	0.04**	0.03**	0.03*	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
College or More	$-0.21^{**}$	$-0.21^{**}$	$-0.21^{**}$	$-0.21^{**}$	$-0.21^{**}$
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Young	0.02**	0.02**	0.02**	$0.02^{*}$	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log(BEA Income)	0.04**	0.04**	$0.04^{*}$	0.04**	0.04**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Increase in House Value	-0.43**	-0.43**	-0.43**	-0.43**	-0.43**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Increase in Loan Balance	0.02	0.02	0.02	$0.03^{*}$	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Payment Resets	0.03**	0.03**	0.03**	0.03**	0.03**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unemployment Rate	$0.02^{'}$	$0.02^{'}$	$0.02^{'}$	$0.02^{'}$	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Income Growth since Origination	-0.16**	-0.16**	-0.16**	-0.16**	-0.16**
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
Observations	25,619,647	25,619,647	25,619,647	25,619,647	25,619,647
	<u> </u>		· · · · · · · · · · · · · · · · · · ·	· · · · · · · · · · · · · · · · · · ·	

Table 11: Hazard Model of Mortgage Delinquency for Subsamples
This table reports the estimates from a Cox proportional hazard model for mortgage delinquency for
the following subsamples: loans with full documentation; loans originated to purchase a new house;
loans used to finance an investment property; non-securitized loans; and loans originated in states
other than California. The significance levels are abbreviated with asterisks: One and two asterisks denote significance at the 5 and 1% level, respectively.

	Full	Purchases	Investment	Not	Exclude
	Documentation	Only	Property	Securitized	California
CM	$0.60^{**}$	$0.85^{**}$	0.65**	0.54**	0.69**
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
$CM \times Log(Income)$	$0.07^{**}$	0.06**	0.04**	0.04**	0.10**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CM x FICO	0.03**	0.02	0.10**	0.19**	0.03*
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
$CM \times LTV$	0.01	-0.09**	-0.09**	-0.04	0.08**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
ARM	0.45**	$0.55^{**}$	$0.37^{**}$	0.11**	$0.47^{**}$
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Log(Income)	-0.14**	-0.12**	$0.02^{*}$	-0.07**	-0.11**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
FICO	-0.71**	-0.68**	-0.69**	-0.77**	-0.69**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LTV	0.48**	$0.44^{**}$	$0.67^{**}$	0.51**	$0.45^{**}$
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
VTI	0.05**	$0.05^{**}$	0.08**	0.04**	0.08**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Low Documentation		0.06**	-0.06**	0.23**	0.03**
		(0.01)	(0.01)	(0.02)	(0.01)
Above Loan Limit	0.26**	0.24**	0.03	0.31**	0.32**
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Condo	-0.06**	-0.09**	-0.16**	-0.11**	-0.10**
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Investment Property	$0.37^{**}$	$0.29^{**}$		0.39**	$0.44^{**}$
	(0.03)	(0.04)		(0.03)	(0.03)
Refinance	0.00		0.24**	0.04	0.06**
	(0.01)		(0.01)	(0.02)	(0.01)
College	-0.19**	-0.26**	-0.23**	-0.23**	-0.20**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Young	0.02	0.03**	0.06**	0.00	$0.02^{*}$
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log(BEA Income)	0.05**	0.06**	0.02	-0.01	0.08**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Increase in House Value	-0.44**	-0.43**	-0.39**	-0.44**	$-0.42^{**}$
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Increase in Loan Balance	-0.01	-0.02	0.11**	0.03	0.06**
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Payment Resets	0.03**	0.03**	0.00	0.02**	0.03**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unemployment Rate	$0.03^{*}$	0.03	-0.01	$-0.03^*$	$0.04^{*}$
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Income Growth since Origination	-0.15**	$-0.17^{**}$	-0.15**	-0.15**	-0.14**
	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)
Observations	9,345,354	15,116,355	2,443,944	2,330,799	21,713,131

Table 12: Variable Definitions and Data Sources

This table reports the description of the variables used and the corresponding data sources.

Variable	Data Source	Aggregation	Description
Loan Amount	LPS	Individual	First-lien loan amount
House Value	LPS	Individual	Appraised home value at origination
Income	HMDA	Individual	Reported Income from loan application
FICO	LPS	Individual	FICO at origination
LTV	LPS	Individual	First lien loan amount divided by appraised value of home
VTI	LPS	Individual	Appraisal value divided by income from loan application
Interest Rate	LPS	Individual	Average initial interest rate
Hypothetical FRM Interest Rate	LPS	Individual	Average interest rate on 30-yr FRM within month, state,
			conforming, LTV, and FICO buckets
Low Documentation	LPS	Individual	Low or no documentation loan indicator variable
Above Conforming Limit	LPS	Individual	Indicator variable for conforming loan.
Government Securitized	LPS	Individual	Securitization indicator variable after one year of loan life
Private Securitized	LPS	Individual	Securitization indicator variable after one year of loan life
Condo	LPS	Individual	Condominium indicator variable
Investment Property	LPS	Individual	Second home or investment property indicator variable
Refinance	LPS	Individual	Refinance indicator variable
With Prepayment Penalty	LPS	Individual	Indicator variable for prepayment penalty along
Prepayment Penalty Term	LPS	Individual	Length in months of prepayment penalty
College	Census	Zip (static)	Proportion of 2000 population with college education or better
Young	Census	Zip (static)	Proportion of 2000 adult population between 20 and 40 years old
House Price Change	FHFA	CBSA-Qtr	Cumulative house price change in the past 5 years
Non-Recourse	Ghent and	State/	States where recourse in residential mortgages is limited by
	Kudlyak (2010)	Individual	the value of the collateral securing the loan. For California,
			only purchase loans are classified as non-recourse.
BEA Income	BLS	$\mathrm{CBSA}\text{-}\mathrm{Qtr}$	Mean income level per capita
Increase in house value	FHFA	Individual	Cumulative house price appreciation at the MSA level since origination.
Increase in loan balance	LPS	Individual	Percentage change in loan balance since origination
Payments Reset	LPS	Individual	Percentage change in minimum monthly mortgage payment since origination
Unemployment Level	BLS	$\mathrm{CBSA}\text{-}\mathrm{Qtr}$	Unemployment rate
Income Growth since Origination	BEA	$\mathrm{CBSA}\text{-}\mathrm{Qtr}$	Growth rate of per capita personal income

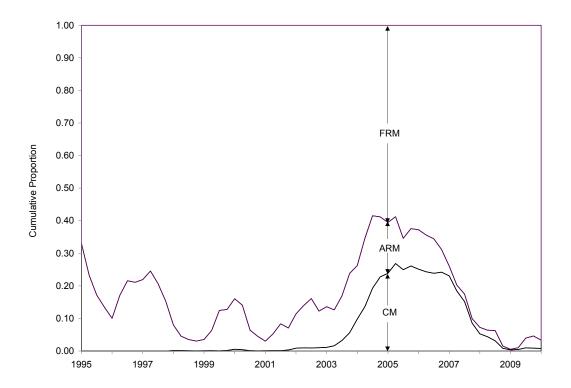
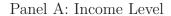
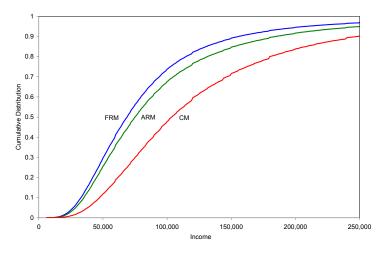


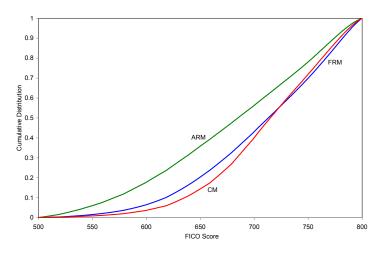
Figure 1: Composition of Mortgage Products.

The figure depicts the composition between Fixed Rate Mortgages (FRM), Adjustable Rate Mortgages (ARM), and Complex Mortgages (CM) over the period between 1995 and 2009.





Panel B: FICO Score



Panel C: VTI Ratio

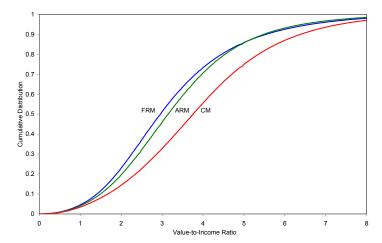
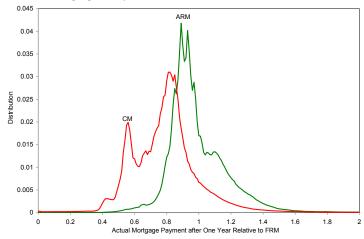
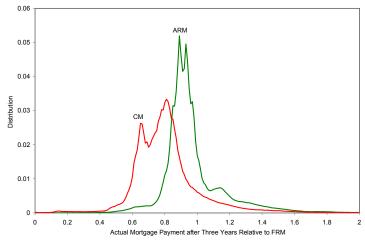


Figure 2: Cumulative Distribution Functions by Mortgage Type These figures depict the cumulative distribution functions of the income level, the FICO score, and the value-to-income ratio (VTI) for Fixed Rate Mortgages (FRM), Adjustable Rate Mortgages (ARM), and Complex Mortgages (CM) over the period between 1995 and 2009.

Panel A: Mortgage Payment After One Year Relative to FRM



Panel B: Mortgage Payment After Three Years Relative to FRM



Panel C: Mortgage Payment After Five Years Relative to FRM

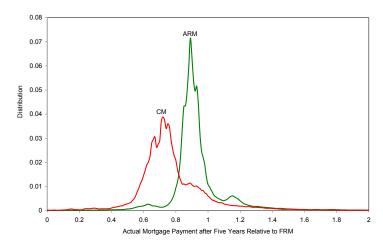
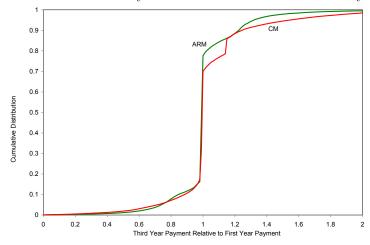


Figure 3: Mortgage Payment Relative to FRM
These figures depict the actual mortgage payments for Adjustable Rate Mortgages (ARM) and for Complex Mortgages (CM) one, three, and five years after origination relative to the mortgage payments of Fixed Rate Mortgages (FRM) with similar borrower characteristics.

Panel A: Third Year Payment Relative to First Year Payment



Panel B: Fifth Year Payment Relative to First Year Payment

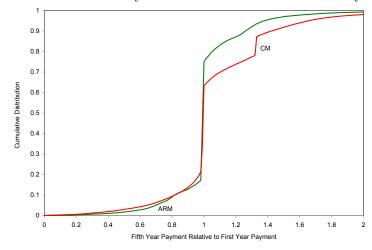
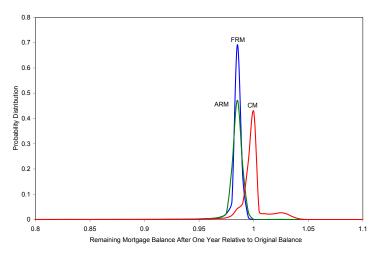
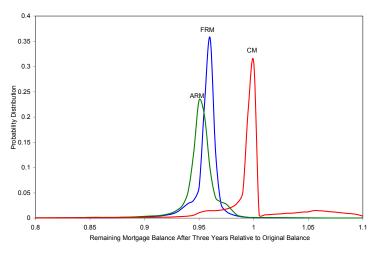


Figure 4: Mortgage Payments Over Time
These figures depict the cumulative distribution functions of the actual mortgage payments for Fixed Rate Mortgages (FRM), Adjustable Rate Mortgages (ARM), and for Complex Mortgages (CM) after three and five years relative to the payments during the first year.

Panel A: Remaining Balance After One Year



Panel B: Remaining Balance After Three Years



Panel C: Remaining Balance After Five Years

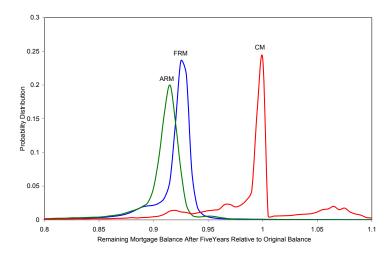


Figure 5: Remaining Mortgage Balances
These figures depict the remaining mortgage balances after one, three, and five years relative
to the initial balances for Fixed Rate Mortgages (FRM), Adjustable Rate Mortgages (ARM),
and Complex Mortgages (CM).

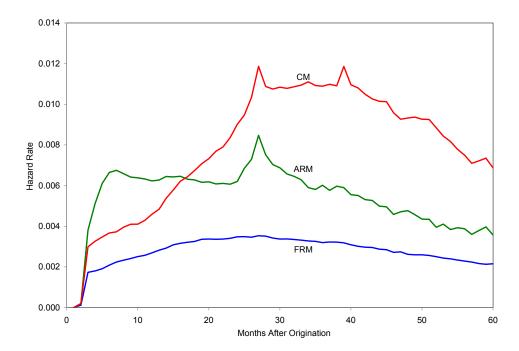


Figure 6: **Proportion of Mortgage Delinquencies by Month After Origination** The figure depicts the proportion of surviving loans that are delinquent by month after orignation for Fixed Rate Mortgages (FRM), Adjustable Rate Mortgages (ARM), and Complex Mortgages (CM) over the period between 2003 and 2009.